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14. ABSTRACT
Research using EEG to discern imagined speech focused on speech loudness envelope reconstruction. Results show that one can use EEG to discern to which of two acoustic speech streams someone is attending. Further results with speech envelopes show that one can use EEG responses to speech loudness envelopes to determine which sentence among a set of possible sentence choices somebody hears or imagines. Work with MEG shows that imagined speech generates motor and auditory imagery as a likely consequence of feedback circuits in use during

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Final Report: Silent spatialized communication among dispersed forces

ABSTRACT

Research using EEG to discern imagined speech focused on speech loudness envelope reconstruction. Results show that one can use EEG to discern to which of two acoustic speech streams someone is attending. Further results with speech envelopes show that one can use EEG responses to speech loudness envelopes to determine which sentence among a set of possible sentence choices somebody hears or imagines. Work with MEG shows that imagined speech generates motor and auditory imagery as a likely consequence of feedback circuits in use during normal speech production. Imagined speech has its strongest effects on hearing speech presented immediately afterward, within a time-frequency window that regulates the comparison between prediction and feedback in speech. Work with fMRI suggests a model for speech prediction with a simulation/estimation stream, possibly involving sensorimotor cortex, and a memory-retrieval stream, possibly involving activity in inferior parietal cortex. Research on intended direction includes a study on the use of EEG to infer the location of covert visual attention in one and two dimensions of space using both visual and auditory stimuli.

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04/15/2015	48.00	Cort Horton, Ramesh Srinivasan, Michael D'Zmura. Envelope responses in single-trial EEG indicate attended speaker in a 'cocktail party', Journal of Neural Engineering, (08 2014): 1. doi: 10.1088/1741-2560/11/4/046015
09/19/2013	39.00	C. Horton, M. D'Zmura, R. Srinivasan. Suppression of competing speech through entrainment of cortical oscillations, Journal of Neurophysiology, (03 2013): 3082. doi: 10.1152/jn.01026.2012
09/19/2013	38.00	David Poeppel, Xing Tian. The Effect of Imagination on Stimulation: The Functional Specificity of Efference Copies in Speech Processing, Journal of Cognitive Neuroscience, (07 2013): 1020. doi: 10.1162/jocn_a_00381
09/19/2013	37.00	Xing Tian, David Poeppel. Mental imagery of speech: linking motor and perceptual systems through internal simulation and estimation, Frontiers in Human Neuroscience, (11 2012): 1. doi: 10.3389/fnhum.2012.00314
10/22/2011	14.00	Samuel Thorpe, Michael D'Zmura, Ramesh Srinivasan. Lateralization of frequency-specific networks for covert spatial attention to auditory stimuli, Brain Topography, (06 2011): 1. doi:
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10/22/2011	17.00	Siyi Deng, Ramesh Srinivasan, Tom Lappas, Michael D'Zmura. EEG classification of imagined syllablerhythm using Hilbert spectrum methods, Journal of Neural Engineering, (06 2010): 1. doi:
10/22/2011	18.00	Siyi Deng, Ramesh Srinivasan. Semantic and acoustic analysis of speech by functional networks with distinct time scales, Brain Research, (05 2010): 132. doi:
10/22/2011	19.00	Xing Tian, David Poeppel, David E. Huber. TopoToolbox: Using Sensor Topography toCalculate PsychologicallyMeaningfulMeasures from Event-Related EEG/MEG, Computer Intelligence and Neuroscience, (02 2011): 1. doi:
11/16/2012	33.00	Xuemin Chi, John Hagedorn, Daniel Schoonover, Michael D'Zmura. EEG-based discrimination of imagined speech phonemes, International Journal of Bioelectromagnetism, (04 2011): 201. doi:
11/16/2012	35.00	Cort Horton, Michael D'Zmura, Ramesh Srinivasan. EEG reveals divergent paths for speech envelopes during selective attention, International Journal of Bioelectromagnetism, (04 2011): 217. doi:

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10/22/2011	27.00	Katharine Brigham, B.V.K. Vijaya Kumar. Imagined Speech Classification with EEG Signals for Silent Communication, Fourth Intl. Conf. Bioinformatics and Biomedical Engineering iCBBE. 18-JUN-10, . : ,
10/22/2011	15.00	Katharine Brigham, B.V.K Vijaya Kumar. Subject identification from electroencephalogram (EEG) signals during imagined speech, IEEE BTAS Conference, Washington, DC. 15-SEP-10, . : ,
10/22/2011	20.00	Xuemin Chi, John B. Hagedorn, Daniel Schoonover, Michael D'Zmura. EEG-Based Discrimination of Imagined SpeechPhonemes, BANFF 2011 - 8th NFSI and ICBEM. 13-MAY-11, . : ,

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02/19/2009	2.00	R. Srinivasan, S. Thorpe, S. Deng, T. Lappas, M. D'Zmura. Decoding attentional orientation from EEG spectra, ( )
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02/20/2012	30.00	Xing Tian, David Poeppel. The effect of imagination on stimulation: the functional specificity of efference copies in speech processing, Neuron (11 2011)
08/04/2009	9.00	X. Tian, D. Poeppel. Motor imagery studied with MEG: Overt versus Covert Finger Movement, ( )
08/04/2009	10.00	S. Deng, R. Srfinivasan. Semantic and acoustic analysis of speech by functional networks with distinct time scales, ( )
08/04/2009	11.00	T. Lappas, M. D'Zmura. Human sensitivity to spatially-patterned amplitude modulation of incoherent noise fields in the horizontal plane , ( )
09/20/2013	43.00	Xing Tian, David Poeppel. Dynamics of self-monitoring and error detection in speechproduction: evidence from mental imagery and MEG, Journal of Cognitive Neuroscience (06 2013)
09/20/2013	44.00	Xing Tian, Jean Mary Zarate, David Poeppel. Mental imagery of speech implicates two processing streams in perceptual prediction, NeuroImage (06 2013)
09/20/2013	45.00	Jean Mary Zarate, Xing Tian, Kevin J.P. Woods, David Poeppel. Multiple levels of linguistic and paralinguistic features contribute to voice recognition, Other (06 2013)
09/20/2013	42.00	Cort Horton, Ramesh Srinivasan, Michael D'Zmura. Envelope responses in single-trial EEG indicate attended speaker in a “cocktail party” , Journal of Neural Engineering (06 2013)
09/20/2013	41.00	Ramesh Srinivasan, Siyi Deng, Michael D’Zmura. Cortical signatures of heard and imagined speech envelopes, Journal of Neural Engineering (09 2013)
10/23/2011	29.00	Cort Horton, Michael D'Zmura, Ramesh Srinivasan. Selective attention and the neural representation of speech envelopes, (10 2011)
11/16/2012	32.00	Xing Tian, David Poeppel. Mental imagery of speech: linking motor and perceptual systems through internal simulation and estimation, Under Revision (10 2012)

11/16/2012	31.00	David Poeppel, Xing Tian. The effect of imagination on stimulation: the functional specificity of efference copies in speech processing, Journal of Cognitive Neuroscience (06 2012)
11/16/2012	36.00	Cort Horton, Michael D'Zmura, Ramesh Srinivasan. Neural Responses to Competing Speech Reveal a Phase-Locking Suppression Mechanism, Journal of Neurophysiology (11 2012)

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Number of Manuscripts:

Books

Received Book

TOTAL:

Received Book Chapter

TOTAL:

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Patents Awarded

Awards

Graduate Students

NAME	PERCENT_SUPPORTED	Discipline
Robert Coleman	0.42	
Andrew Z. Wisti	0.33	
Michael D. Nunez	0.04	
Thom Lappas	0.25	
Siyi Deng	0.20	
Amir Moghimi	0.33	
Kathy Brigham	0.33	
Samuel Thorpe	0.16	
Cort Horton	0.20	
Javi Garcia	0.04	
Daniel Schoonover	0.33	
Akshay Chandrasekharan	0.04	
FTE Equivalent:	**2.67**	
Total Number:	**12**	

Names of Post Doctorates

NAME	PERCENT_SUPPORTED
Cort Horton	0.17
Xing Tian	0.50
Xuemin Chi	0.33
John Hagedorn	0.37
Siyi Deng	0.16
FTE Equivalent:	**1.53**
Total Number:	**5**

Names of Faculty Supported

NAME	PERCENT_SUPPORTED	National Academy Member
Ramesh Srinivasan	0.19	
Thomas D'Zmura	0.26	
David Poeppel	0.09	
Greg Hickok	0.07	
Rich Stern	0.06	
Kumar Bhagavatula	0.06	
FTE Equivalent:	**0.73**	
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Names of Under Graduate students supported

NAME	PERCENT_SUPPORTED	Discipline
Alvin Li	0.01	Psychology
Trevor Hummel	0.01	Psychology
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Names of Personnel receiving masters degrees

NAME	
Thom Lappas	
Siyi Deng	
Samuel Thorpe	
Cort Horton	
Javi Garcia	
Robert Coleman	
Daniel Schoonover	
Kathy Brigham	
Amir Moghimi	
Total Number:	**9**

Names of personnel receiving PHDs

NAME	
Robert Coleman	
Thom Lappas	
Siyi Deng	
Amir Moghimi	
Kathy Brigham	
Samuel Thorpe	
Cort Horton	
Javi Garcia	
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NAME	PERCENT_SUPPORTED
FTE Equivalent:	
Total Number:	

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Scientific Progress

Technology Transfer

FINAL REPORT

ARO 54228-LS-MUR
Silent Spatialized Communication Among Dispersed Forces

University of California, Irvine
Carnegie Mellon University
New York University
2008-2014

Michael D'Zmura
April 15, 2015

TABLE OF CONTENTS

List of Figures 3

1. Overview 4

2. Scientific Results 4

2A. Imagined Speech 4

2B. Intended Direction 16

3. References 21

LIST OF FIGURES

Figure 1. Results of MEG studies by Tian & Poeppel on imagined movement and imagined speech suggest that an internal forward model underlies mental imagery of speech.	5
Figure 2. Producing articulation imagery (top left) generates in MEG a topography (scalp response pattern) that differs from that associated with overt articulation (bottom topography).	6
Figure 3. Efference copies generated during speech production generate internal predictions which may be compared to auditory feedback to determine whether there are errors in speech production that need to be addressed.	7
Figure 4. Dual stream prediction model (DSPM).	8
Figure 5. The envelope of the TIMIT(sx) sentence number 37, "critical equipment needs proper maintenance", shows how loudness varies as a function of time for this particular speaker.	9
Figure 6. Comparison of the spectrogram, wavelet scalogram and Hilbert spectrum of the same time series.	10
Figure 7. Source localization results for one of the subjects show the cortical distributions of the two strongest EEG components in which are found envelope following responses (EFRs).	12
Figure 8. Classification performance as a function of (left plot) heard EEG data duration for each of the eight subjects and (right plot) imagined EEG data duration for each of eight subjects.	12
Figure 9. Trial time course for the Coordinate Response Measure experiment.	13
Figure 10. Locations and frequency of occurrence of the most informative electrodes found across the three classifications and across all days of data collection for the seven subjects in the CRM experiment.	14
Figure 11. Envelope-EEG cross-correlations.	15
Figure 12. Classification accuracy is plotted as a function of EEG sample length for each of three different classifiers that make use of different features in the EEG.	16
Figure 13. The experiment design in the work by Thorpe *et al*. (2011).	17
Figure 14. Induced alpha band power is shown averaged over the cue and interstimulus intervals for left-cued (LC) and right-cued (RC) attention conditions, respectively.	18
Figure 15. The topographies of random forest classifier permutation feature importance indicate that right lateralized occipito-parietal alpha and low-beta power are the predominant features used to reliably predict covert visual attention location along the azimuth.	19
Figure 16. Mobile subject Hagedorn with red EEG gel cap controls navigation of robot (center).	20

1. OVERVIEW

Project goals were to improve the basic neuroscientific understanding of imagined speech and intended direction and to develop signal-processing methods relevant to their decoding from brain imaging data. We used non-invasive brain-imaging methods: electroencephalography (EEG), magnetic resonance imaging (MRI), and magneto-encephalography (MEG). Project research was conducted by faculty, post-docs, graduate students, and undergraduate students at three academic institutions: the University of California, Irvine (UCI), Carnegie Mellon University (CMU), and New York University (NYU). Work at UCI focused on EEG studies of imagined speech and of intended direction. Work at CMU focused on analysis of EEG data collected at UCI. Work at NYU focused on MEG and fMRI studies. This report presents scientific results in Section 2, auxiliary information in Section 3, and bibliographic references in Section 4.

2. SCIENTIFIC RESULTS

The first section presents results for imagined speech (Section 2A). It covers work at NYU on an efference copy model for speech production, which provides for the generation of articulatory and auditory imagery during imagined speech, and experimental evidence in its favor. It then turns to work with EEG at UCI and CMU. This work focuses primarily on the use of machine learning methods to determine circumstances under which EEG provides information about imagined speech.

The second section presents results for intended direction (Section 2B). Experimental work at UCI shows that the direction of attention to auditory stimuli stimulates brain networks similar to those found when directing attention to visual stimuli. It shows also that the bottom-up direction of attention to a visual target generates signals in EEG which may be used to infer where the target is located in the visual field. Finally, work with BCIs has led to successful demonstrations of navigation in virtual environments and of robot remote control using brain waves.

2A. IMAGINED SPEECH

Project results for imagined speech include the development of an efference copy model of speech production (Tian & Poeppel, 2010, 2012). The model describes the brain's generation of the auditory and motor imagery that one experiences while imagining speech. Efference copy models feed voluntary motor commands back to various brain centers so that the predicted effects of these voluntary actions on the organism, including changes in what is sensed, can better be taken into account. This kind of model dates back to Von Helmholtz and was put on a firm footing by the work of Von Holst and Mittelstaedt (1950) and Sperry (1950) on motor control and visuomotor coordination.

Efference copy model. The Tian & Poeppel (2010, 2012) model is shown in Figure 1. Motor commands concerning speech production are copied and sent to a module that helps to predict the resulting motor state. If there is a significant difference between sensed and predicted motor states (*e.g.*, a situation encountered when one is talking with one's mouth full), then motor planning can be changed appropriately. The motor efference copy also allows for prediction of the sensory effects of speech production. A perceptual efference copy is used to predict what will be heard when speech motor actions are carried out. The motor state estimation and sensory prediction processes are thought to be associated with motor imagery and auditory perceptual imagery, respectively, during imagined speech production. This assumption lets the efference copy model link speech production and imagined speech production.

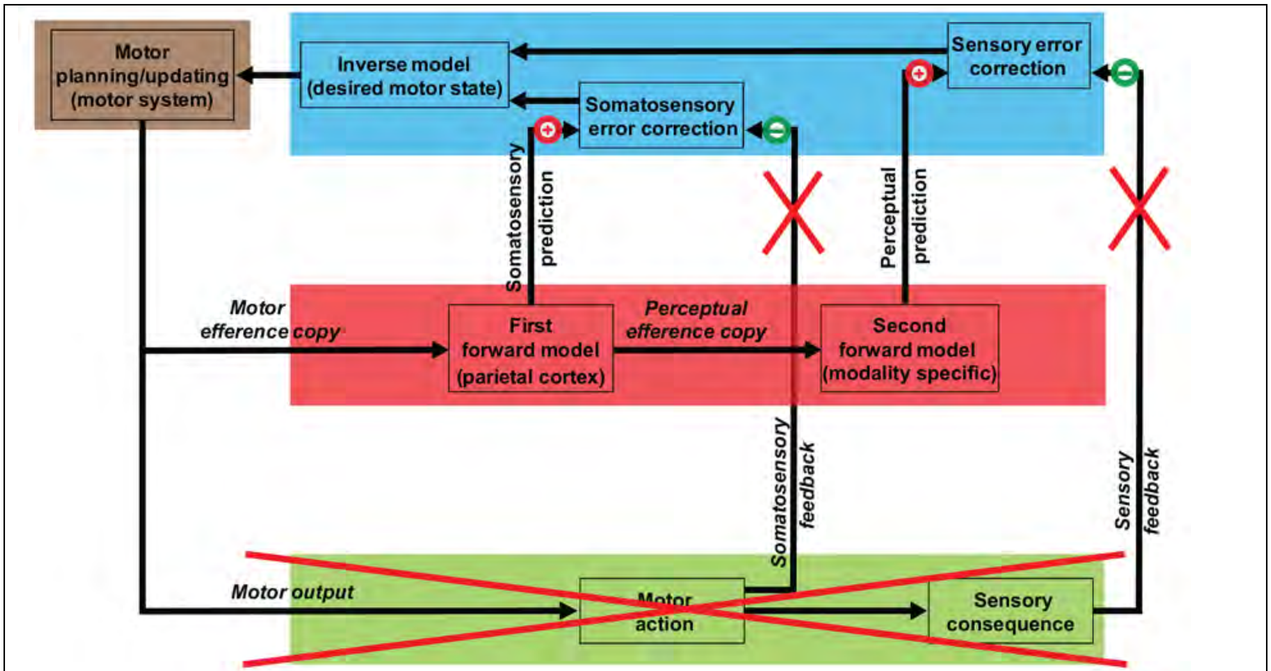


Figure 1. Results of MEG studies by Tian & Poeppel on imagined movement and imagined speech suggest that an internal forward model underlies mental imagery of speech. The motor systems that mediate action preparation carry out the same functions in the mental imagery of speech, but only perform motor simulation, in the sense that the planned motor commands are truncated along the path to primary motor cortex and are not executed (the red cross over external outputs). A copy of such planned motor commands is processed internally and is used to estimate the associated somatosensory consequences. A copy of the somatosensory estimate is sent on to modality-specific areas, and the perceptual consequences that would be produced by the overt action are estimated. Imagery associated with articulator movement and auditory perception during imagined speech is held by the model to be the result of residual activity from these internal estimation processes and is linked to the absence of cancellation from external feedback (marked by the red Xs over somatosensory and sensory feedback pathways). After Tian & Poeppel (2012).

MEG topographies found while imagining speech. The model is supported by a variety of experimental results on speech using MEG (Tian & Poeppel, 2010, 2012, 2013, 2015). One such result (Tian & Poeppel, 2010) is shown in Figure 2. MEG topographies found when imagining speech articulation or when imagining speech auditory perception resemble those found when actually hearing speech. This provides nice evidence in favor of the model shown in Figure 1.

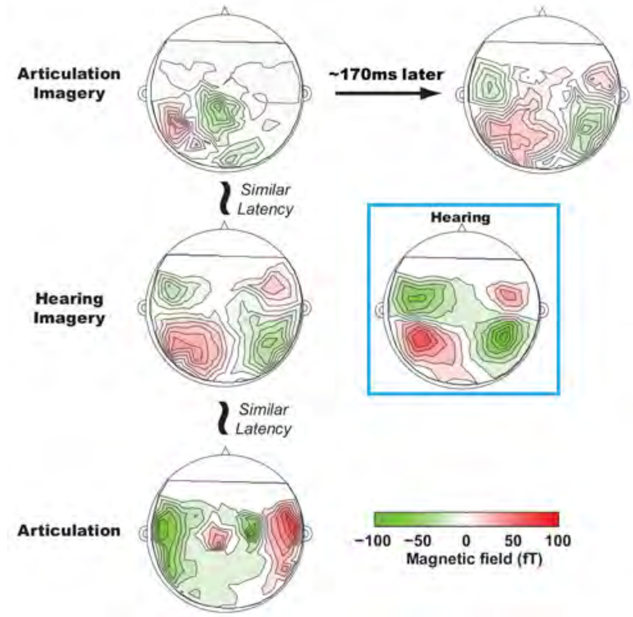


Figure 2. Producing articulation imagery (top left) generates in MEG a topography (scalp response pattern) that differs from that associated with overt articulation (bottom topography). Yet producing articulation imagery by imagining speaking leads shortly thereafter (170 msec) to a response topography (top right) that resembles strongly that associated with hearing speech (middle right). Likewise, when one produces hearing imagery by imagining hearing speech, the resulting topography (middle left) resembles that found when hearing actual speech (middle right).

Time-frequency window for use of speech production predictions. An MEG study by Tian and Poeppel (2015) introduces further evidence in favor of the model. Tian and Poeppel argue that a critical subroutine of self-monitoring during speech production is to detect any deviation between expected and actual auditory feedback. They investigated the associated neural dynamics using MEG recording in mental-imagery-of-speech paradigms. Participants covertly articulated the vowel /a/; their own (individually recorded) speech was played back, with parametric manipulation using four levels of pitch shift, crossed with four levels of onset delay. A non-monotonic function was observed in early auditory responses when the onset delay was shorter than 100 msec. Suppression was observed for normal playback, but enhancement for pitch-shifted playback. However, the magnitude of enhancement decreased at the largest level of pitch shift that was out of pitch range for normal conversion, as suggested in two behavioral experiments. No difference was observed among different types of playback when the onset delay was longer than 100 msec.

These results suggest that the prediction suppresses the response to normal feedback, which mediates source monitoring (see Figure 3). When auditory feedback does not match the prediction, an “error term” is generated, which underlies deviance detection. Tian & Poeppel (2015) suggest that a frequency window (addressing spectral differences) and a time window (constraining temporal differences) jointly regulate the comparison between prediction and feedback in speech.

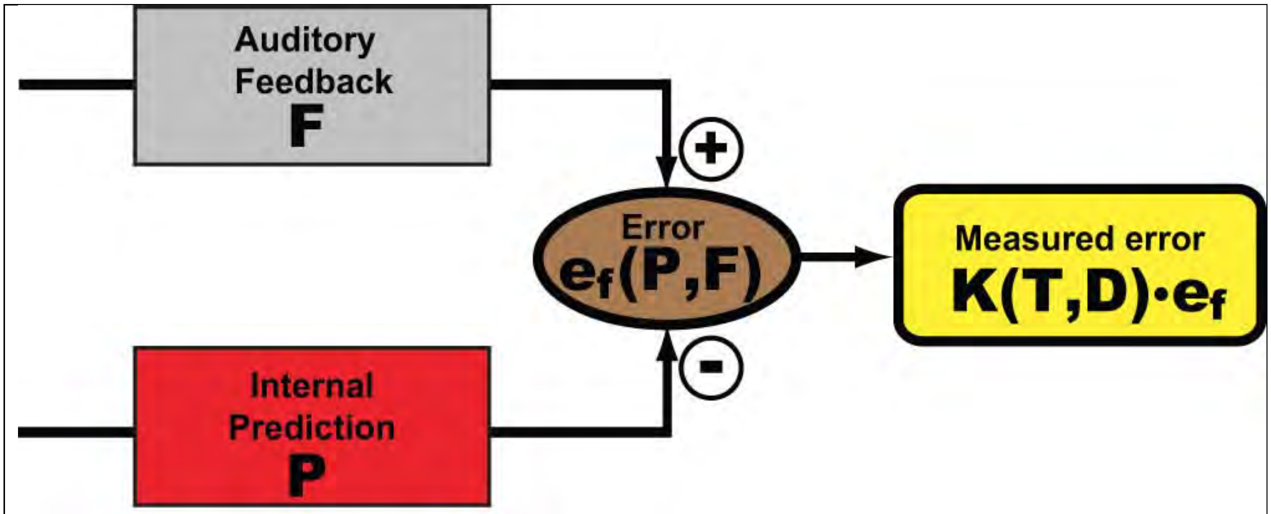


Figure 3. Efference copies generated during speech production generate internal predictions which may be compared to auditory feedback to determine whether there are errors in speech production that need to be addressed. Results of an MEG experiment suggest that the error term is evaluated within a time/frequency window (Tian & Poeppel, 2015).

Dual-stream model of speech production prediction. In work as yet unpublished, team members at NYU performed an fMRI experiment in which they establish that two processing streams are likely to underlie perceptual prediction in imagined speech production.

Subjects performed two speech imagery tasks -- articulation imagery (AI) and hearing imagery (HI) -- designed to differentially recruit the two streams. As shown in Figure 4, AI induced greater activity in the simulation-estimation stream, including sensorimotor cortex, subcentral (BA 43), middle frontal cortex (BA 46) and supramarginal gyrus (SMG), suggesting more recruitment of simulation and estimation functions. Moreover, AI showed more activation in posterior superior temporal sulcus compared with HI, suggesting that precise auditory representation can be obtained via simulation-estimation mechanisms. On the other hand, distributed memory networks, including middle frontal (BA 8), inferior parietal cortex and intraparietal sulcus, were more activated during HI compared to AI, suggesting a role for the memory-retrieval prediction pathway in the HI task.

These results demonstrate that neural systems implement motor simulation-estimation and memory retrieval as two distinct mechanisms to internally construct corresponding perceptual outcomes. These two mechanisms serve as a foundation for predicting perceptual changes, either via an established causal relationship between actions and their perceptual consequences or via stored perceptual experiences of environmental regularity.

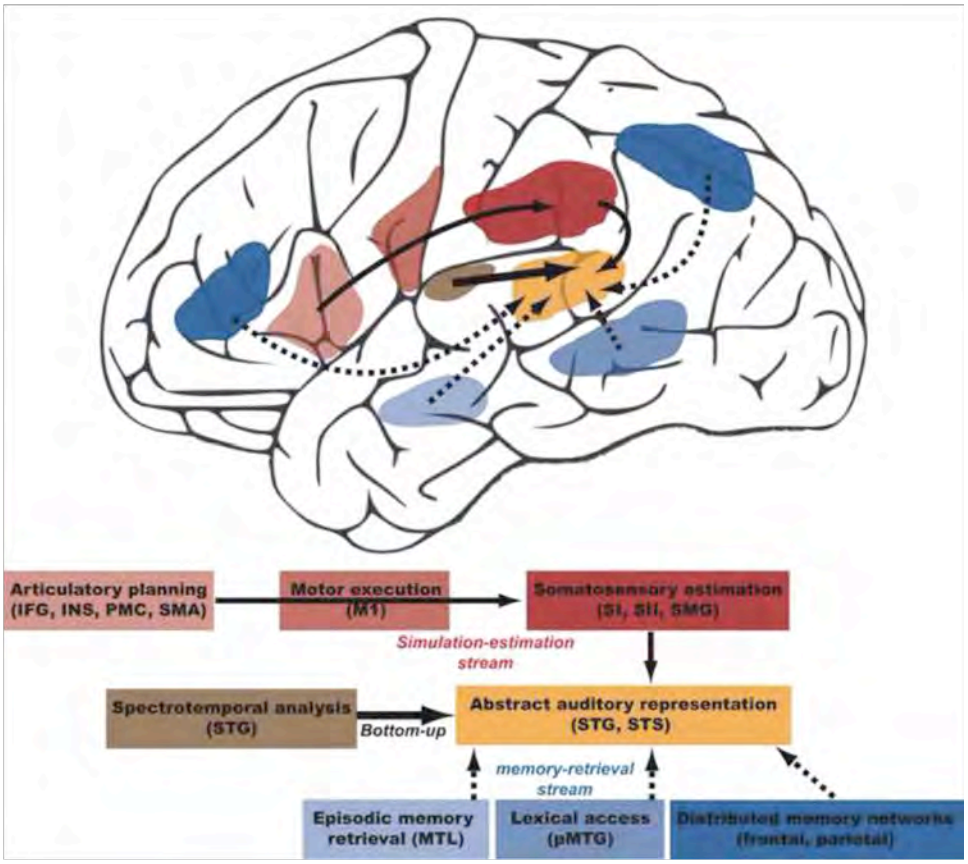
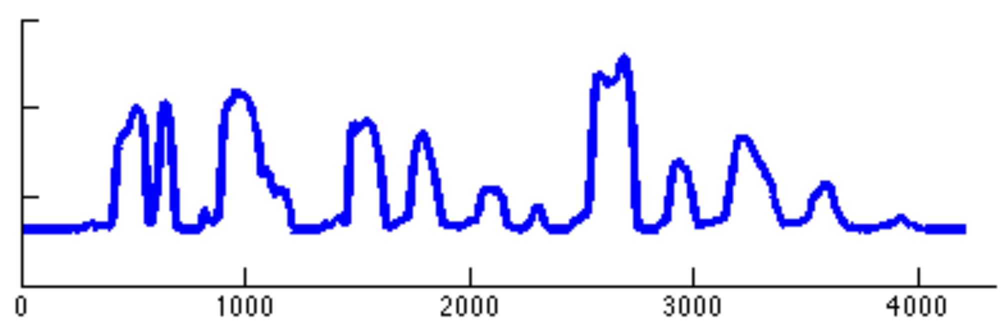


Figure 4. Dual stream prediction model (DSPM). Top: approximate cortical regions in the hypothesized dual streams. Bottom: schematic diagram of the DSPM (color scheme corresponds to the anatomical locations above). The abstract auditory representations (orange) can be induced from both bottom-up and top-down processes and are formed around regions of STG and STS. The top-down induction process can be carried out in either the memory-retrieval or simulation estimation prediction pathway. The memory-retrieval stream (blue) includes pMTG, MTL and distributed frontal-parietal networks, for retrieval from long-term lexical items, episodic and semantic memory, respectively. The simulation-estimation stream (red) includes the frontal motor system and parietal somatosensory system. The articulatory trajectory is planned in frontal motor regions, including IFG, PMC, INS and SMA. If covert production is the goal, the planned articulation signal bypasses M1 and is simulated internally. The somatosensory consequence of the simulated articulation is estimated over parietal somatosensory regions, including SI, SII and SMG. The auditory consequences -- in the form of an abstract auditory representation – is derived from the subsequent estimation. A highly specified auditory representation (thick arrow) is obtained in the bottom-up perceptual process that goes through spectrotemporal analysis of external stimuli in STG (brown). The stream that the motor simulation and perceptual estimation processes are available can enrich the specificity of predicted auditory representations (solid arrows), compared to enrichment from memory retrieval stream (dotted arrows). Abbreviations: STG, superior temporal gyrus; STS, superior temporal sulcus; pMTG, posterior middle temporal gyrus; MTL, middle temporal lobe; IFG, inferior frontal gyrus; PMC, premotor cortex; INS, insula; SMA, supplementary motor area; M1, primary motor cortex; SI, primary somatosensory cortex; SII, secondary somatosensory cortex; and SMG, supramarginal gyrus. After Tian, Zarate, & Poeppel (submitted).

Imagined speech identification. EEG experiments on speech production show that one can use EEG traces of the heard or the imagined speech loudness envelope to determine which speech stream one is listening to or imagining, respectively (Deng *et al*., 2010). There are also positive results for distinguishing imagined words and sentences (Lappas, 2011) and imagined phonemes (Brigham & Vijaya Kumar, 2010) on the basis of information other than loudness envelope. Furthermore, experimental results show also that one can use EEG traces of speech loudness envelopes to determine the speech stream to which one is paying attention (Horton *et al*., 2011, 2013, 2014).

Loudness envelope information in EEG. An early EEG experiment on imagined speech at UCI involved imagined sentences drawn from the TIMIT(sx) database. A pilot set of EEG data collected in early fall 2008 was analyzed to determine whether any electrode waveforms bore traces of the temporal envelope of the acoustic speech waveform heard during the cue period of the trial. Such an envelope is illustrated in Figure 5. Six sentences drawn from the timit(sx) database were used. Signal processing methods involving the Hilbert-Huang transform let one detect the envelope in EEG signals when a subject is listening to speech. This analysis was applied to an existing, full dataset in a study of steady-state auditory evoked potentials (SSAEP). When listening to speech in this SSAEP experiment, instantaneous frequencies extracted by a Hilbert-Huang transform are correlated with the envelope of the speech signal (Deng & Srinivasan, 2010). The same methods were used to determine whether there were any electrodes with waveforms correlated to the envelope of the acoustic speech waveform during the *imagined* speech period of the trial in the pilot dataset: yes. What this means intuitively is that the varying loudness of a sentence (pattern of stress) is echoed in EEG both when one listens to that sentence and when one imagines the sentence.



CRITICAL EQUIPMENT NEEDS PROPER MAINTENANCE

Figure 5. The envelope of the TIMIT(sx) sentence number 37, "critical equipment needs proper maintenance", shows how loudness varies as a function of time for this particular speaker.

Imagined speech rhythm identification using EEG. Analysis of data from the "BaKu" experiment shows that one can use EEG to determine the rhythm with which syllables are produced in imagination (Deng *et al*., 2010). An initial analysis of high-density EEG data from the BaKu experiment, in which two syllables (/ba/ and /ku/) were spoken in imagination in one of three rhythms, showed that information concerning imagined speech is present in EEG alpha (9-12Hz), beta (13-18Hz) and theta (3-8Hz) bands. Discovering in the BaKu data informative spectral features within bands led to follow-on work with the Hilbert-Huang transform (Huang *et al*., 1998), spearheaded by former UCI grad student Siyi Deng. This analysis focused on using predictive classification of envelopes to decode the rhythm with which imagined syllables are produced. A modified Second Order Blind Identification (SOBI) algorithm was used to help enhance the signals and reduce dimensionality (Cardoso, 1998; Tang *et al*., 2005). The SOBI algorithm uses the consistent temporal structure along multi-trial EEG data to blindly decompose the original recordings into a set of neuroanatomically-grounded components. These SOBI components possess broad spatial distributions across the scalp that distinguish left/right, front/back, *etc*. In Deng's work, joint temporal and spectral features were extracted from the Hilbert spectra of selected SOBI components, after performing a Hilbert-Huang transform.

Hilbert spectra of empirical mode components provide accurate time-spectral representations of non-stationary data that are sparser than representations provided by conventional techniques like short-time Fourier spectrograms and wavelet scalograms (see Figure 6). Predictive classification of the three rhythms yields good results for inter-trial transfer, with performance for all seven subjects lying at a significantly greater than chance level.

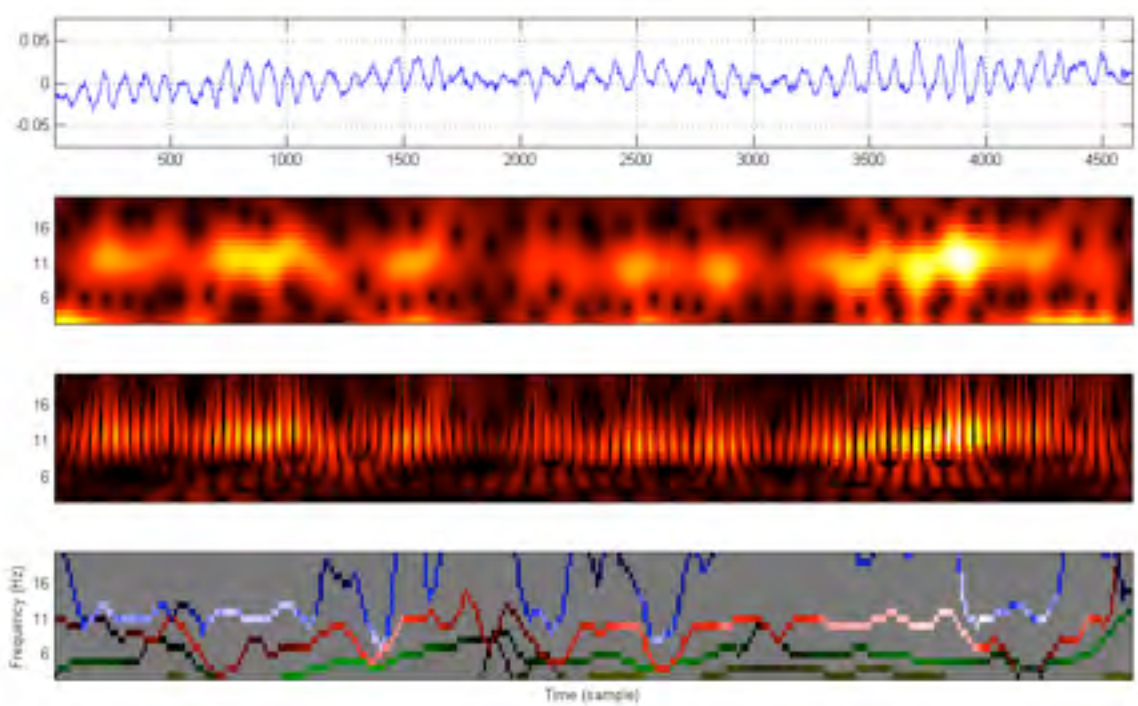


Figure 6. Comparison of the spectrogram, wavelet scalogram and Hilbert spectrum of the same time series. Top plot: Original time-varying EEG signal from SOBI output. Second plot: Short-time Fourier transform spectrogram. Third plot: Morlet wavelet spectrogram. Bottom plot: Hilbert spectrum, projected onto an 18Hz by 384 time-point grid. Note that the Hilbert spectrum representation is considerably sparser than that of the STFT and wavelet spectrograms.

The paper that describes the application of the empirical mode decomposition to the identification of BaKu trial rhythm (Deng *et al*., 2010) refers also to the successful use of class-averaged spectrograms. An advantage of this latter method is that it can be implemented as a real-time classification procedure for a brain-computer interface. The method finds the average spectrogram generated in trials of various classes and orthogonalizes these spectrograms to produce spectrogram matched filters. Matched filter outputs on a particular trial, found by computing a scalar product of the matched filter spectrogram and the trial spectrogram, are used to classify the trial: the matched filter producing the largest scalar product output identifies the trial class. While the classification performance for BAKU rhythm found using class-averaged spectrograms is poorer than that found using the SOBI/HHT methods, the margin is not wide. Furthermore, its electrode-by-electrode analysis lets one identify informative electrodes for particular subjects. The identification provides no evidence for a single set of informative scalp locations common to all subjects.

The results suggest that the rhythmic structure of imagined syllable production can be detected in non-invasive brain recordings, and provide a step toward the development of an EEG-based system for communicating imagined speech.

Deng and colleagues (2010) reported negative results for determining which of two syllables was imagined in the BaKu experiment using empirical mode decomposition or matched filter methods. However, CMU graduate student Kathy Brigham and Kumar Bhagavatula succeeded in classifying /ba/ and /ku/ trials (Brigham & Vijaya Kumar, 2010). They were able to classify imagined syllables using data preprocessing methods which relied on Hurst exponents to remove trials and electrodes deemed to contain artifacts (*e.g.*, electromyographic). A large number of trials and electrodes were removed. The remaining trials were used to determine whether /ba/ and /ku/ may be discriminated from one another using EEG. Results varied from "not at all" to a high of 88% classification success (*vs*. 50% guessing rate), depending on subject.

Heard and imagined sentence identification using EEG. Having obtained his doctoral degree, UC Irvine Associate Specialist Dr. Siyi Deng completed a further, as yet unpublished, study on whether EEG can be used to determine which sentence someone listens to or produces in imagination (Deng *et al*., submitted). The study focused on the loudness envelope of speech (its loudness as a function of time) and its representation in EEG signals to determine whether sentences can be discriminated on the basis of the EEG representation of their loudness envelopes.

The experiment used both heard and imagined speech to determine whether cortical signatures of heard speech can be used to identify imagined speech. Each trial in the experiment presented one of six possible spoken sentences; it was both heard and, immediately afterwards, produced in imagination. The analysis focused on the use of envelope following responses (EFRs) to identify heard sentences and to identify imagined sentences. Common to both analyses was the employment of source imaging methods to find the cortical origins of EFRs to heard speech. Reconstructing the EEG from the strongest sources of the EFRs in parietal and temporal cortex, shown in Figure 7, improved the correlation between EEG and the amplitude envelope of the heard speech.

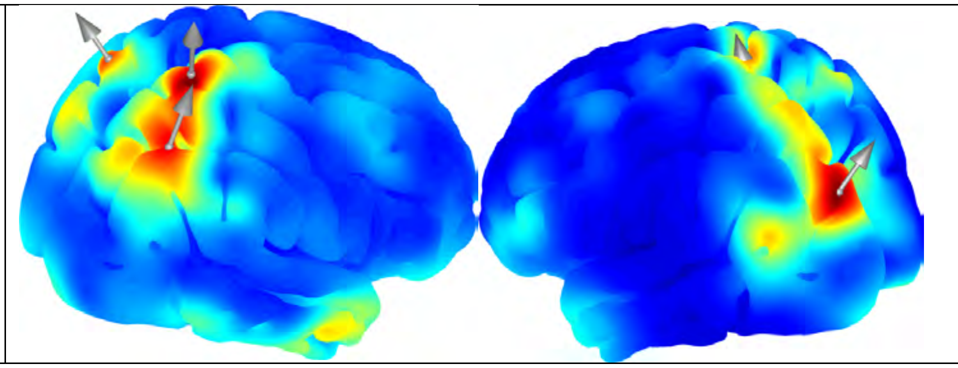


Figure 7. Source localization results for one of the subjects show the cortical distributions of the two strongest EEG components in which are found envelope following responses (EFRs). These sources are illustrated using a color scale in which red indicates the greatest strength. The strongest sources, found in parietal and temporal cortex, are used to find the cortical origins of EFRs to heard speech and to estimate the EEG generated by these sources.

Single-trial classification performance with the heard sentences was found to be statistically significant for two of eight subjects. Significant classification performance was found for *all* subjects when one used EEG data from multiple trials of the same sentence, concatenated to produce data of greater duration. The improvement in classification with heard speech duration is shown in the left panel of Figure 8. In order to classify EEG recordings of imagined speech, activities at the cortical sources determined for heard speech were estimated from EEG data recorded while speech was imagined. Referring to the right panel of Figure 8, one sees that classification performance with imagined sentences improves as the duration of EEG data increases. About seven trials of the same sentence are required for classification of the imagined sentence to reach statistical significance. These results suggest imagining speech engages some of the cortical populations involved in perceiving speech, as suggested by models of speech perception and production.

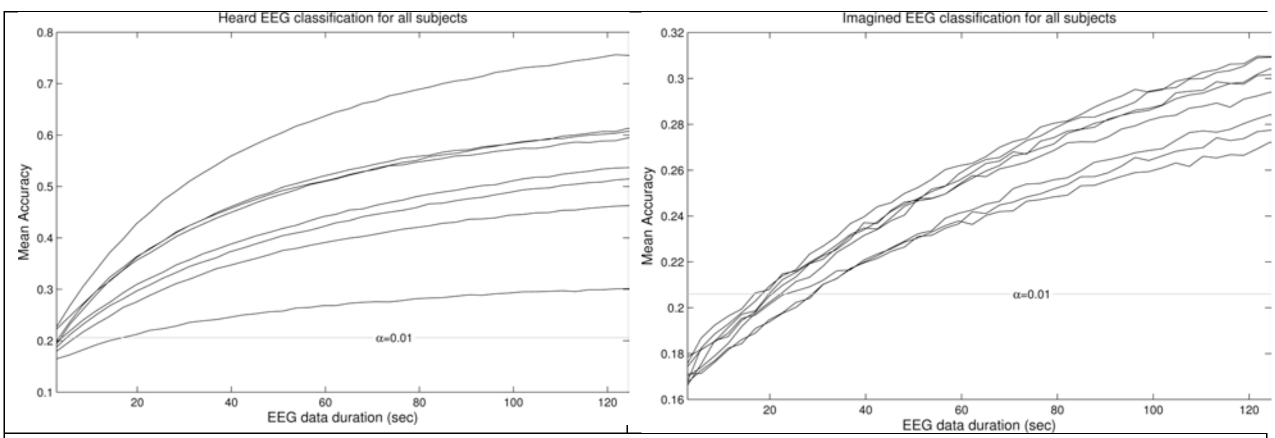


Figure 8. Classification performance as a function of (left plot) heard EEG data duration for each of the eight subjects and (right plot) imagined EEG data duration for each of eight subjects. Note the different vertical scales for the plot of heard sentence classifiability (left) and imagined sentence classifiability (right). Each curve shows the results for one subject. Measurements for trials using the same sentence were concatenated to produce segments of longer duration.

Imagined word and sentence identification using EEG. The final chapter of Dr. Thom Lappas' dissertation (Lappas, 2011) reports the results of an experiment on the use of EEG to determine which of six possible "Coordinate Response Measure" sentences a subject was imagining. Six sentences that vary in callsign and color words were used: "Ready [callsign] go to [color] now", with three callsign words "baron", "eagle" and "tiger" and two color words "red" and "green". Each trial started with one of the six possible sentences presented aloud (the cue). The cue period was followed at a set interval by two clicks to help subjects produce the cued sentence in imagination during the targeted production period (see Figure 9). The initial second in each trial produced EEG that was used to normalize the power spectrum, for each trial and channel. EEG recorded during the trial period 4.3 - 7.2 sec were then subject to sequential feature analysis with the aim of determining which channels, times and frequencies are most informative when performing a six-way classification of single trials. Leave-one-out cross-validation was used to determine classification performance rates.

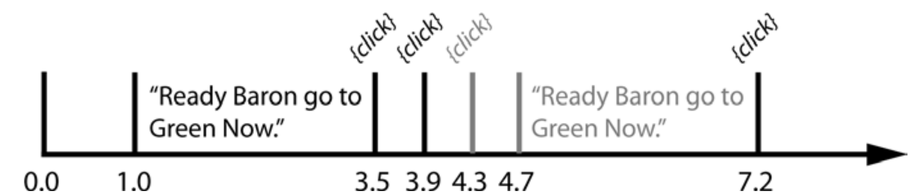
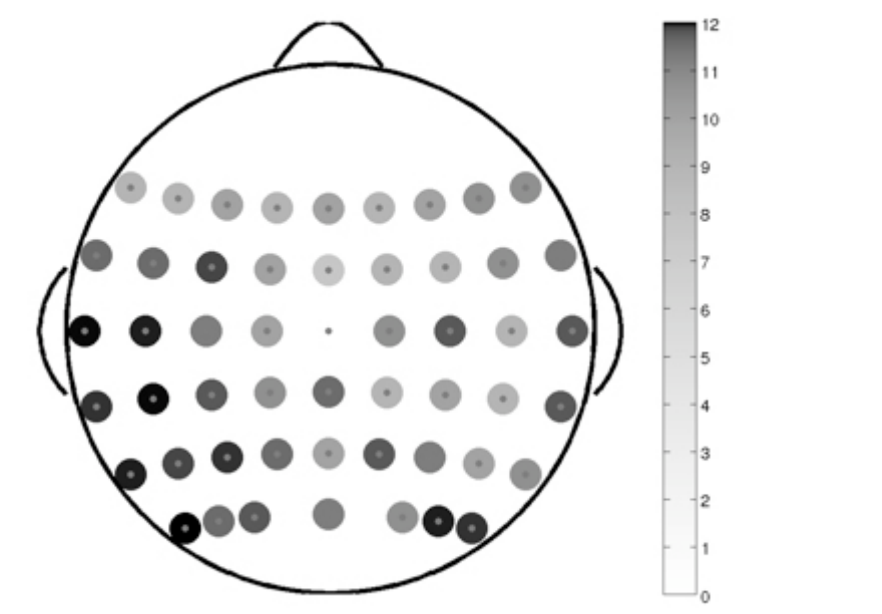


Figure 9. Trial time course for the Coordinate Response Measure experiment. The cued sentence was heard aloud; these auditory stimuli were recorded beforehand in the subject's own voice. After two clicks, subject's task was to reproduce the cued sentence in imagination with the onset indicated above. EEG data were analyzed during the period 4.3 - 7.2 sec.

Six-way sentence classification performance rates found for each subject's daily data, using these most informative features, are highly significant. Three of the subjects had days on which performance rates exceeded 50%, a level three times the guessing rate 16%. Three-way classification of callsign words was highly significant for all subjects and reached 70% and 73% for the top two subjects, which compares favorably to the guessing rate 33%. Finally, two-way classification of color words was highly significant for all subjects and reached 83% and 84% for the top two, which compares favorably to the guessing rate 50%. While the most informative features varied across subjects and days, aggregating informative features across subjects and experimental sessions shows that the most informative channels tend to lie over temporal cortex, especially temporal cortex in the left hemisphere (see Figure 10).

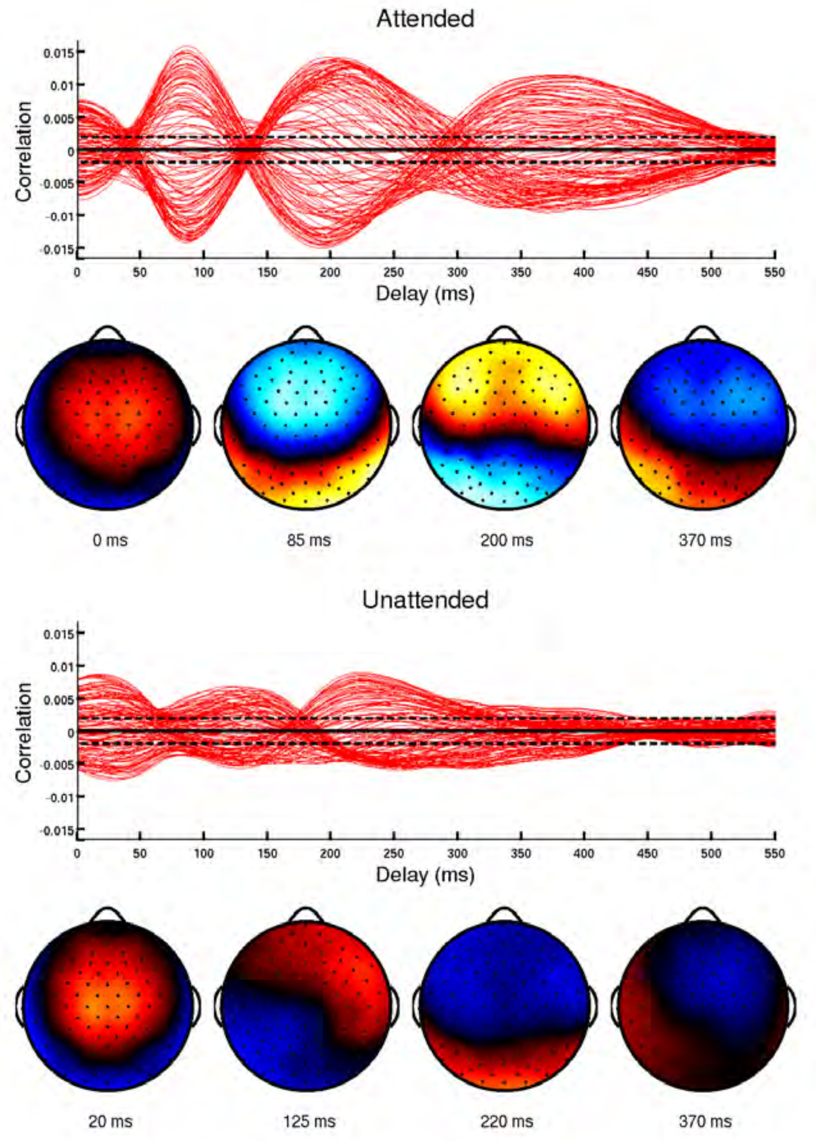
Figure 10. Locations and frequency of occurrence of the most informative electrodes found across the three classifications and across all days of data collection for the seven subjects in the CRM experiment. The colorbar at right relates disk color to the frequency of occurrence of a particular electrode location in the aggregate list of informative features.



Use of EEG to determine who somebody is listening to. As part of his dissertation work, UC Irvine graduate student Cort Horton studied the information found in EEG while a person listens to one of two or more speakers (Horton *et al*., 2013). Recent studies report activity in auditory cortex that is phase-locked to the envelope of speech, but it remains unclear whether this phase-locked representation requires comprehension, how it interacts with attention, and the extent to which it is hemispherically lateralized. EEG was recorded from 10 adults while they selectively attended to amplitude-modulated speech coming from one speaker, while ignoring speech from another. Detailed timing and topographic information about the envelope representations was extracted by cross-correlating the attended and unattended stimulus envelopes with each channel of EEG, as well as components produced *via* ICA decomposition of the data.

Results show that the envelopes of both attended and unattended speech are encoded in the EEG, including several lateralized responses (see Figure 11). However, there are large differences between the attended and unattended cross-correlation functions. In addition, trial stimuli were amplitude-modulated at 40 and 41 Hz in order to induce steady-state responses. Those steady-state responses were *not* affected by attention. The data suggest that mechanisms for selective attention to one of multiple speakers involves frequency-band limited enhancement *and suppression*, as well as a modulation of the phase of endogenous theta activity in auditory cortex to align high-excitability periods with attended speech syllables.

Figure 11. Envelope-EEG cross-correlations. Plots of the grand-averaged correlation between each channel of EEG with the stimulus envelopes as a function of lag. Each trace represents a separate channel of EEG. The dashed lines indicate the 0.5th and 99.5th percentile of correlation values observed in the control condition. Several delays in the cross-correlation functions are further illustrated with topographic plots underneath. Warm colors denote correlations with positive potentials, while cool colors denote correlations with negative potentials.



Horton and colleagues (2015) extended the result by investigating the accuracy with which a subject's locus of attention during a "cocktail party" task can be ascertained from speech loudness envelope responses present within single trials of EEG. It was found that the attended speaker can be determined reliably from short periods of EEG, with accuracy improving as a function of trial length. Furthermore, the performance of this speech loudness envelope-based attention classifier was compared to others based on changes in steady-state responses (elicited via 40 and 41 Hz amplitude modulations of the speech) and hemispheric lateralization of alpha power. We found that the neural responses to the speech loudness envelopes were far more robust indicators of attention than the others. Figure 12 shows that the use of EEG identified as informative through cross-correlation with speech stimulus envelopes (leftmost panel) leads to strong classification results, while the use of alpha lateralization indices (middle panel) or auditory steady-state response magnitudes (rightmost panel) do not. These results suggest that envelope-related signals recorded in EEG data can be used to form robust auditory BCIs that do not require artificial manipulation (*e.g.*, amplitude modulation) of stimuli in order to function.

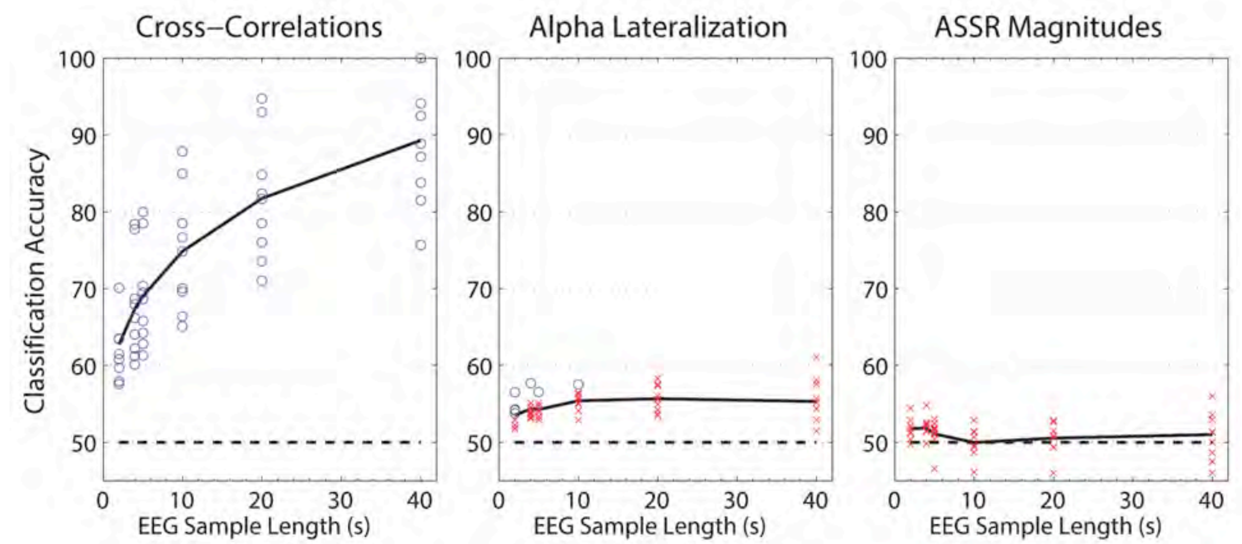


Figure 12. Classification accuracy is plotted as a function of EEG sample length for each of three different classifiers that make use of different features in the EEG. The mean accuracies for each subject are indicated by the individual data points, with the subject mean indicated by the black line. Chance is marked with the dashed line at 50% classification accuracy. Significantly above-chance accuracy values are marked by blue circles, while non-significant values are indicated by red crosses. Measures of the hemispheric lateralization of alpha power provide poor classification accuracy (middle plot), as do magnitudes of auditory steady-state responses to modulations at 40 and 41Hz (right plot). Cross-correlations between EEG and speech loudness envelopes provide a robust means to extract information that produces accurate determination of whether one is covertly paying attention to the speaker heard through the left ear or the speaker heard through the right ear.

2B. INTENDED DIRECTION

Project research on intended direction included work on covert attention that bears some similarities to the just-discussed work on the direction of attention to particular speech streams. The difference is that the studies to be discussed in this section necessitate the direction of attention in a particular spatial direction. An overt shift of attention is accompanied by eye, head, and body movements. Covert shifts are not evident. Yet covert shifts have been shown for decades to influence performance: enhance speed and accuracy in tasks involving stimuli that lie in the covertly-attended direction.

An experiment with EEG showed that one can use EEG to determine whether one is attending to a speech stream at left or one at right (Thorpe *et al*., 2011). Results suggest that attention to auditory stimuli activates brain networks similar to those activated during the direction of visual attention. A study of covert attention to visual stimuli used EEG to perform a visual perimetry based on the bottom-up direction of attention (Coleman, 2014). Results not only replicate earlier ones for the lateralization of EEG response in occipital cortex based on target presence in left or right visual hemifield, but also demonstrate a vertical gradient in occipital cortical EEG activity that depends on visual target vertical position.

EEG signals concerning the direction of attention to auditory stimuli. UCI graduate student conducted ARO MURI-supported work as part of his dissertation research (Thorpe *et al*., 2011). A cued spatial attention experiment was conducted to investigate the time-frequency structure of human EEG induced by attentional orientation of an observer in external auditory space. Attention was cued to one of two spatial locations, at left and right, respectively (see Figure 13). Subjects were instructed to report the speech stimulus at the cued location and to ignore a simultaneous speech stream originating from the uncued location. Analysis used wavelet spectra to normalize response in each EEG frequency band by the mean level observed in the early part of the cue interval, with the aim of measuring induced power related to the deployment of attention.

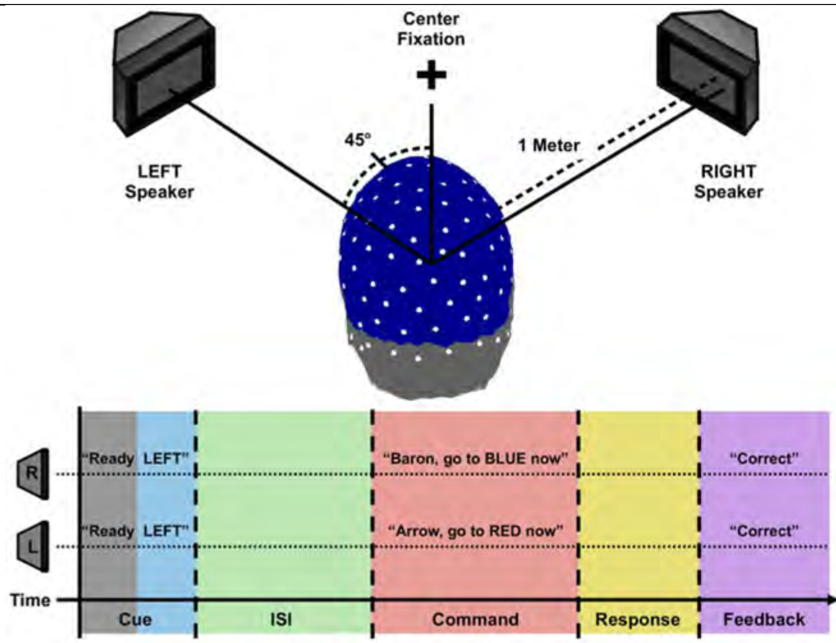


Figure 13. The experiment design in the work by Thorpe *et al*. (2011). Above is shown the physical layout of the experiment. Each speaker was 45 deg away from fixation and could not be seen by an observer without moving the eyes. Below is shown the trial time course. In the example shown, the subject is cued to attend to the left speaker. After a variable interstimulus interval (ISI, from 500-1500 msec), two different sentences are played through the speakers. The subject's task is to indicate the codeword and color word played from the cued speaker. The volume of the uncued speaker is high enough to necessitate strict attention to sound in the direction of the cued speaker.

Topographies of band-specific induced power during the cue and inter-stimulus intervals showed peaks over the symmetric bilateral scalp areas (see Figure 14 for the alpha power band result). Results suggest that the deployment and maintenance of spatially-oriented attention through a period of 1100 msec is marked by distinct episodes of reliable hemispheric lateralization ipsilateral to the direction in which attention is oriented. An early theta lateralization was evident over posterior parietal electrodes and was sustained through the interstimulus interval. In the alpha and mu bands, punctuated episodes of parietal power lateralization were observed roughly 500 msec after attentional deployment, consistent with previous studies of visual attention. In the beta band, these episodes show similar patterns of lateralization over frontal motor areas. These results indicate that spatial attention involves similar mechanisms in the auditory and visual modalities.

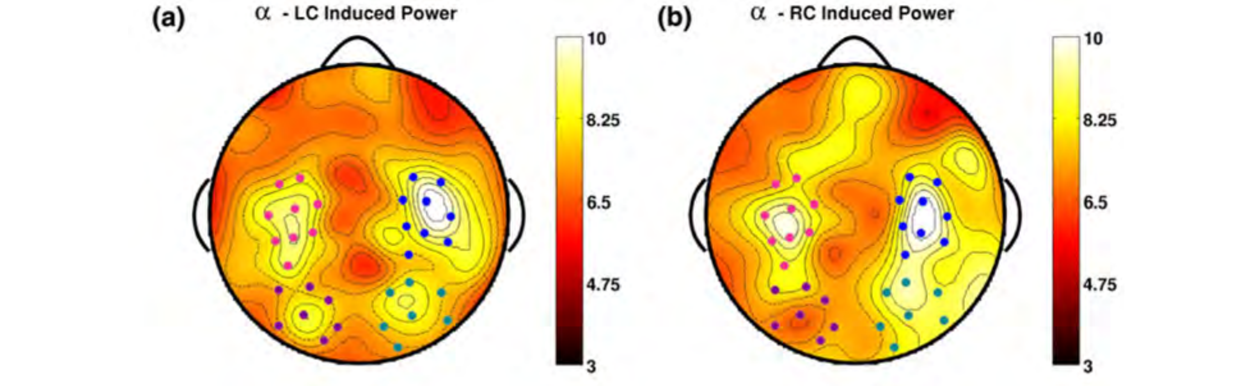


Figure 14. Induced alpha band power is shown averaged over the cue and interstimulus intervals for left-cued (LC) and right-cued (RC) attention conditions, respectively. Two pairs of symmetric channel groups appear as peaks in the resultant power band topographies. These are situated over bilateral motor (pink/blue dots for LC/RC, respectively) and parietal areas (magenta/cyan dots for LC/RC, respectively).

Use of EEG to track bottom-up visual attention in two dimensions. UCI graduate student Robert Coleman studied visual attention in his MURI-supported dissertation work (Coleman, 2014). His results suggest that EEG may be used to discern the covert direction of visual attention in one or two dimensions. Subjects in an EEG experiment sat in front of a monitor and maintained fixation on the center of the monitor's screen while directing attention covertly to a sequence of target letters. For each presentation, the subjects responded with a button press to indicate target identity. Visual targets were the single letters A, F, H, or L. Each letter was presented for 1500 msec and was followed immediately by the next letter. Target locations varied in three different ways to provide three experimental conditions:

1. the targets varied in *horizontal* position, with positions drawn from a uniform distribution on the range [-19.2, 19.2] degrees of visual angle (deg); these were vertically centered and varied in azimuth;
2. the targets varied in *vertical* position, with positions drawn from a uniform distribution on the range [-19.2, 19.2] deg; these were horizontally centered and varied in elevation;
3. target position varied in *two dimensions*, with positions drawn from a uniform distribution on the square [-19.2, 19.2] deg x [-19.2, 19.2] deg in the center of the display.

Analysis used common spatial pattern features from 64 channel EEG measured within alpha (8-12Hz), low-beta (16-20 Hz) and high-beta (22-26Hz) bands and within 350-600 msec of target presentation onset (see figure 15). To determine how well EEG can be used to determine letter location, the range of letter locations was divided into two, three, or five equal-sized intervals for the horizontal and vertical conditions, and was divided into four or nine equal-sized square sectors for the 2D condition. Support vector machine and 50-tree random forest classifiers were used to classify trials from two subjects according to target letter position. Classifications into two, three or five sectors in horizontal and vertical conditions were statistically significant for both subjects; classifications into four or nine sectors in the 2D condition were also significant.

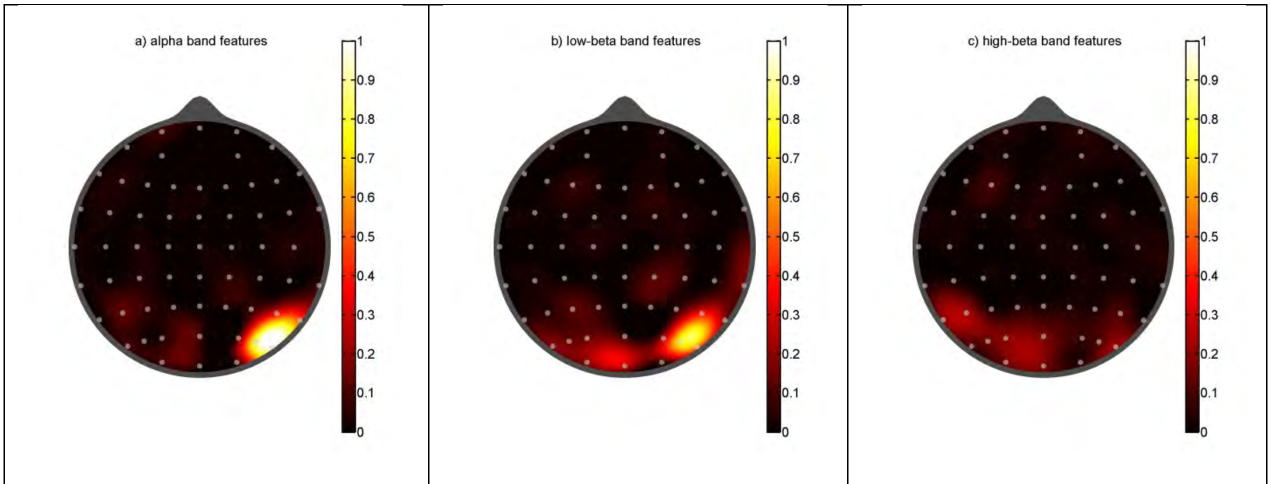


Figure 15. The topographies of random forest classifier permutation feature importance indicate that right lateralized occipito-parietal alpha and low-beta power are the predominant features used to reliably predict covert visual attention location along the azimuth. Data from the horizontal condition and the 2D condition were used to generate these topographies. A similar analysis suggests that central occipito-parietal low-beta power is the most important feature when identifying vertical location.

The overall result is that EEG can be used to passively detect the spatial position of visual attention, at varying degrees of precision, as a person attends to objects they see.

EEG-based BCI for movement control. In a first stage of this project, software for the action game Quake 2 was modified to receive and act on movement control signals provided by EEG signal-processing software. The EEG signal-processing software was trained to recognize neural activity, generated by the user of the brain-computer interface, meant to signal turn left, turn right, go, or stop. A naive Bayes classifier was used to process data from a brief training experiment in which the user signaled these four categories without any movement. We were able to demonstrate successful navigation through a Quake 2 game level using brain waves with these methods.

We next extended these methods to handle robot control. Graduate research assistant Zack Wisti, aided by Associate Specialist John Hagedorn and by D'Zmura, implemented robot romote control by mobile human subjects. A custom-built, portable, tetherless, 64-electrode EEG system by ANT and acquired using DURIP funding is worn in a backpack by a mobile human subject. A laptop computer within the backpack performs EEG-based brain-computer interface signal processing. The signal-processing computer is connected wirelessly to a computer onboard the robot (see Figure 16).

A simple navigational scheme was used to control turns to left and right and to control stopping and starting. Measurements of alpha power in left hemisphere and right hemisphere electrodes, respectively, are used for control. The measured difference in alpha power between left and right hemispheres is used to cause either left or right turns by the robot. Likewise, the total alpha power in left and right hemispheres is used to modulate speed. A high alpha power signals relaxation or closed eyes and is a natural signal for stopping. Reduction in alpha due to alertness causes the robot to start moving forward again.

Figure 16. Mobile subject Hagedorn with red EEG gel cap controls navigation of robot (center). A signal-processing computer within the backpack worn by the subject communicates wirelessly with a computer onboard the robot. EEG signals are processed by the computer in the backpack to control the robot's left/right turns and starting/stopping. Subject's task is to cause the robot to navigate a full lap of a slalom course marked by orange pylons.

3. REFERENCES

Brigham, K. & Vijaya Kumar, B.V.K. (2010). Imagined speech classification with EEG signals for silent communication: a preliminary investigation into synthetic telepathy. *Fourth International Conference on Bioinformatics and Biomedical Engineering (iCBBE)* 1-4.

Brigham, K. & Vijaya Kumar, B.V.K. (2010b). Subject identification from electroencephalographam (EEG) signals during imagined speech. *Fourth IEEE International Conference on Biometrics Theory, Applications and Systems,* 1-7.

Cardoso, J. F. (1998). Blind signal separation: statistical principles. *Proc. IEEE* **86**, 2009-2025.

Chi, X., Hagedorn, J.B., Schoonover, D. & D'Zmura, M. (2011). EEG-based discrimination of imagined speech phonemes. *Proceedings of the BANFF 2011 - 8th NFSI and ICBEM*, May, 2011, 1-6.

Coleman, R. (2014). *Use of EEG to track visual attention in two dimensions*. Ph.D. Dissertation, University of California, Irvine.

Deng, S. (2010). *Dynamic correlates of perceiving and imagining speech*. Ph.D. Dissertation, University of California, Irvine.

Deng, S. & Srinivasan, R. (2010). Semantic and acoustic analysis of speech by functional networks with distinct time scales. *Brain Research* **1346**, 132-144.

Deng, S., Srinivasan, R., Lappas, T. & D'Zmura, M. (2010). EEG classification of imagined syllable rhythm using Hilbert spectrum methods. *Journal of Neural Engineering,* 7, 046006.

Deng, S., Srinivasan, R. & D'Zmura, M. (submitted). Cortical signatures of heard and imagined speech envelopes. *J. Neural Engineering*.

D'Zmura, M., Deng, S., Lappas, T., Thorpe, S. & Srinivasan, R. (2009). Toward EEG sensing of imagined speech. Jacko, J.A. (Ed.), *Human-Computer Interaction, Part I, HCII 2009, LNCS 5610* (Berlin: Springer) 40-48.

Hickok, G. & Poeppel, D. (2007). The cortical organization of speech processing. *Nature Reviews Neuroscience* **8**, 393-402.

Von Holst, E., and Mittelstaedt, H. (1950). Das reafferenz prinzip. (Wechselwirkungen zwischen Zentralnervensystem und Peripherie.) *Die Naturwissenschaften* **37**, 464-476.

Horton, C., D'Zmura, M. & Srinivasan, R. (2011). Electrophysiological representation of speech envelopes during selective attention. *Proceedings of the BANFF 2011 - 8th NFSI and ICBEM*, May, 2011, 1-4.

Horton, C., D'Zmura, M. & Srinivasan, R. (2011). EEG reveals divergent paths for speech envelopes during selective attention. *International Journal of Biomagnetism* **13(4)**, 217-222.

Horton, C., D'Zmura, M. & Srinivasan, R. (2013). Suppression of competing speech through entrainment of cortical oscillations. *J. Neurophysiology* **109**, 3082-3093.

Horton, C., Srinivasan, R. & D'Zmura, M. (2014). Envelope responses in single-trial EEG indicate attended speaker in a "cocktail party". *J. Neural Engineering* ***11***, 1-12.

Huang, N. E., Shen, Z., Long, S. R., Wu, M. C., Shih, H. H., Zheng, Q., Yen, N.-C., Tung, C.C., & Liu, H. H. (1998, March). The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. In *Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences,* **454(1971)**, 903-995.

Lappas, T. (2011). *Investigations in speech and audition*. Ph.D. Dissertation, University of California, Irvine.

Sperry, R. W. (1950). Neural basis of the spontaneous optokinetic response produced by visual inversion. *Journal of comparative and physiological psychology* **43(6)**, 482.

Srinivasan, R., Thorpe, S., Deng, S., Lappas, T. & D'Zmura, M. (2009). Decoding attentional orientation from EEG spectra. Jacko, J.A. (Ed.), *Human-Computer Interaction, Part I, HCII 2009, LNCS 5610* (Berlin: Springer) 176-183.

Tang, A. C., Liu, J.-Y. & Sutherland, M. T. (2005). Recovery of correlated neuronal sources from EEG: the good and bad ways of using SOBI. *Neuroimage* **28**, 507-519.

Thorpe, S., D'Zmura, M. & Srinivasan, R. (2011). Lateralization of frequency-specific networks for covert spatial attention to auditory stimuli. *Brain Topography*, doi:10.1007/s10548-011-0186, 1-16.

Tian, X. & Poeppel, D. (2010). Mental imagery of speech and movement implicates the dynamics of internal forward models. *Frontiers in Psychology*, doi:10.3389/fpsyg.2010.00166, 1-23.

Tian, X., Poeppel, D. & Huber, D.E. (2011). TopoToolbox: Using sensory topography to calculate psychologically meaningful measures from event-related EEG/MEG. *Computational Intelligence and Neuroscience* **2011**, doi:10.1155/2011/674605, 1-8.

Tian, X., & Poeppel, D. (2012). Mental imagery of speech: linking motor and sensory systems through internal simulation. *Front. Hum. Neurosci.* 6:314. doi: 10.3389/fnhum.2012.00314.

Tian, X. & Poeppel, D. (2013). The effect of imagination on stimulation: the functional specificity of efference copies in speech processing. *Journal of Cognitive Neuroscience* 2013 Mar 7

Tian, X., & Poeppel, D. (2015). Dynamics of self-monitoring and error detection in speech production: evidence from mental imagery and MEG. *Journal of Cognitive Neuroscience* **27(2)**, 352-364.

Tian, X., Zarate, J.M. & Poeppel, D. (submitted). Mental imagery of speech implicates two processing streams in perceptual prediction. *Neuroimage*.